

# *Regionally Specific Drivers of Land-Use Transitions and Future Scenarios*

A SYNTHESIS CONSIDERING THE LAND  
MANAGEMENT INFLUENCE IN THE  
SOUTHEASTERN US



# Co-Investigators and Students

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**Virginia Tech:** V.A. Thomas, R.H. Wynne, R.Q. Thomas, C. Blinn

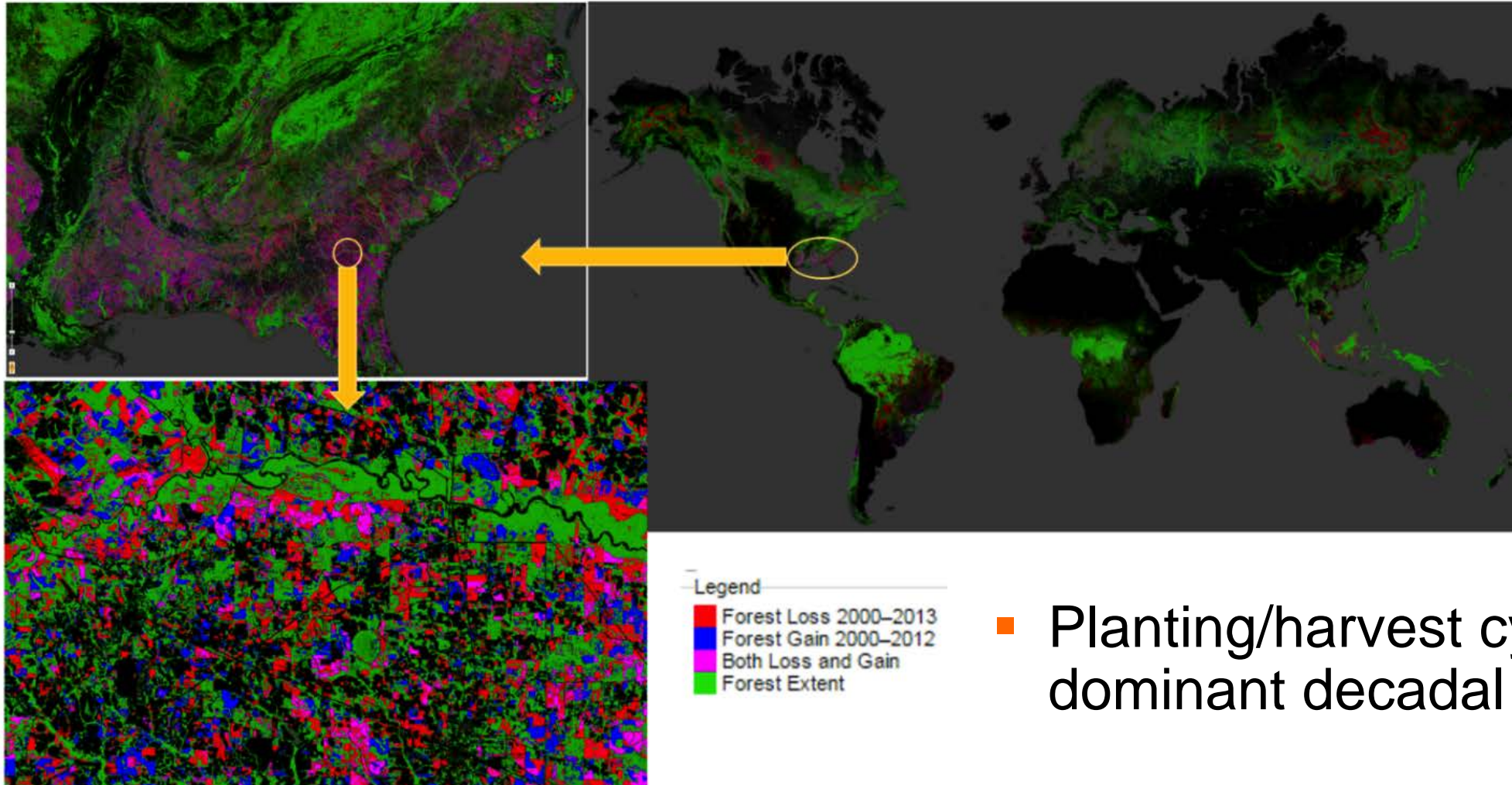
J. Kauffman, E. Brooks, P. Williams, W. McCurdy, M. House

**University of Maryland:** L. Chini

**University of Georgia:** R.B. Mei

**USDA Forest Service:** D. Wear

# *In the southeastern US, forests are dynamic*



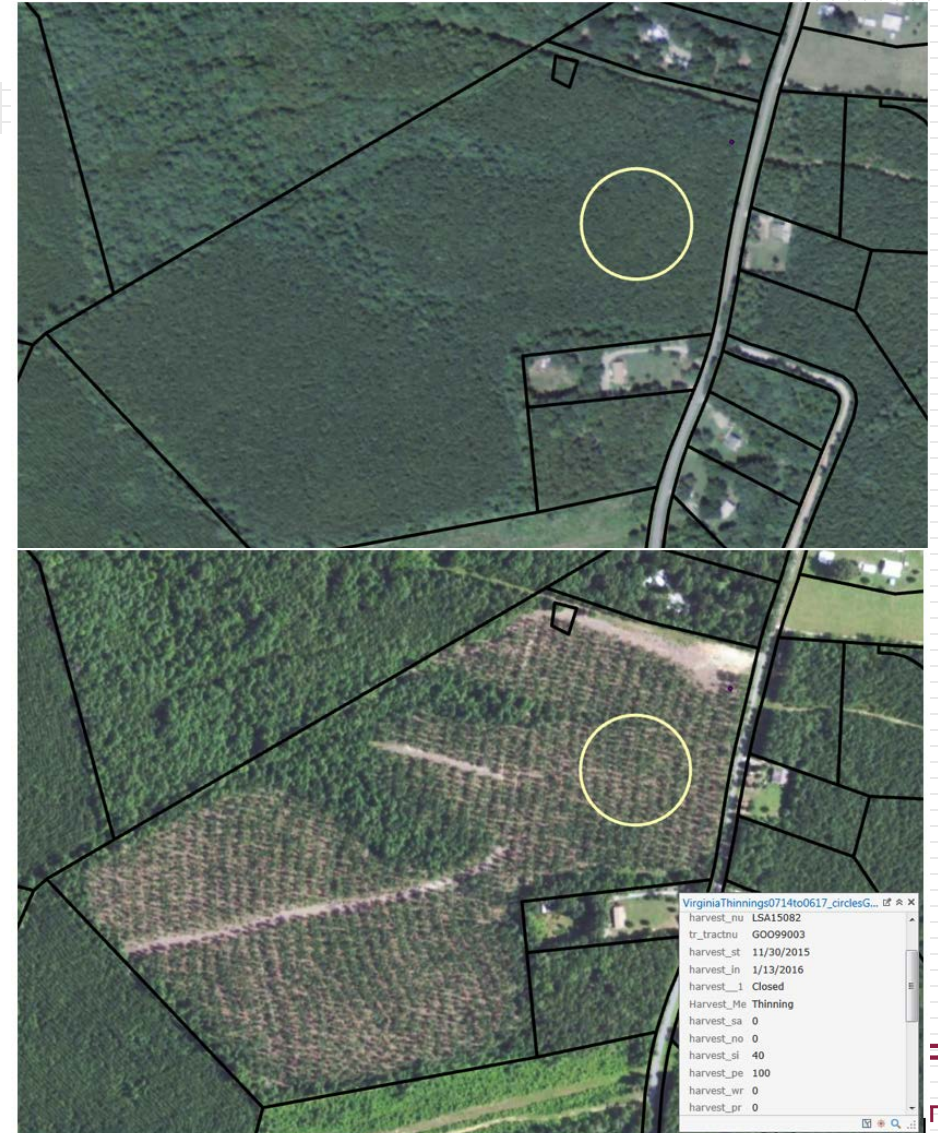
Derived from Hansen et al (2013)

- Planting/harvest cycle dominant decadal signal

# Two major land change patterns in the region

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- Land-use changes
  - Forest  $\leftrightarrow$  Agriculture
  - Forest  $\rightarrow$  Developed (urban)
  - Agriculture  $\rightarrow$  Developed (urban)
- Periodic land cover changes reflecting forest management
  - Harvest, regeneration
  - Changes in density/composition
    - Naturally regenerating hardwoods  $\rightarrow$  planted pine



## *2 parallel approaches to modeling past and future land use change*


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- Globally gridded land-use change products
- Regional, expert driven socioeconomic analysis
- a limiting feature of previous studies has been the treatment of secondary forests as a single land use
  - lumping passively managed or unmanaged forests with those that are intensively managed

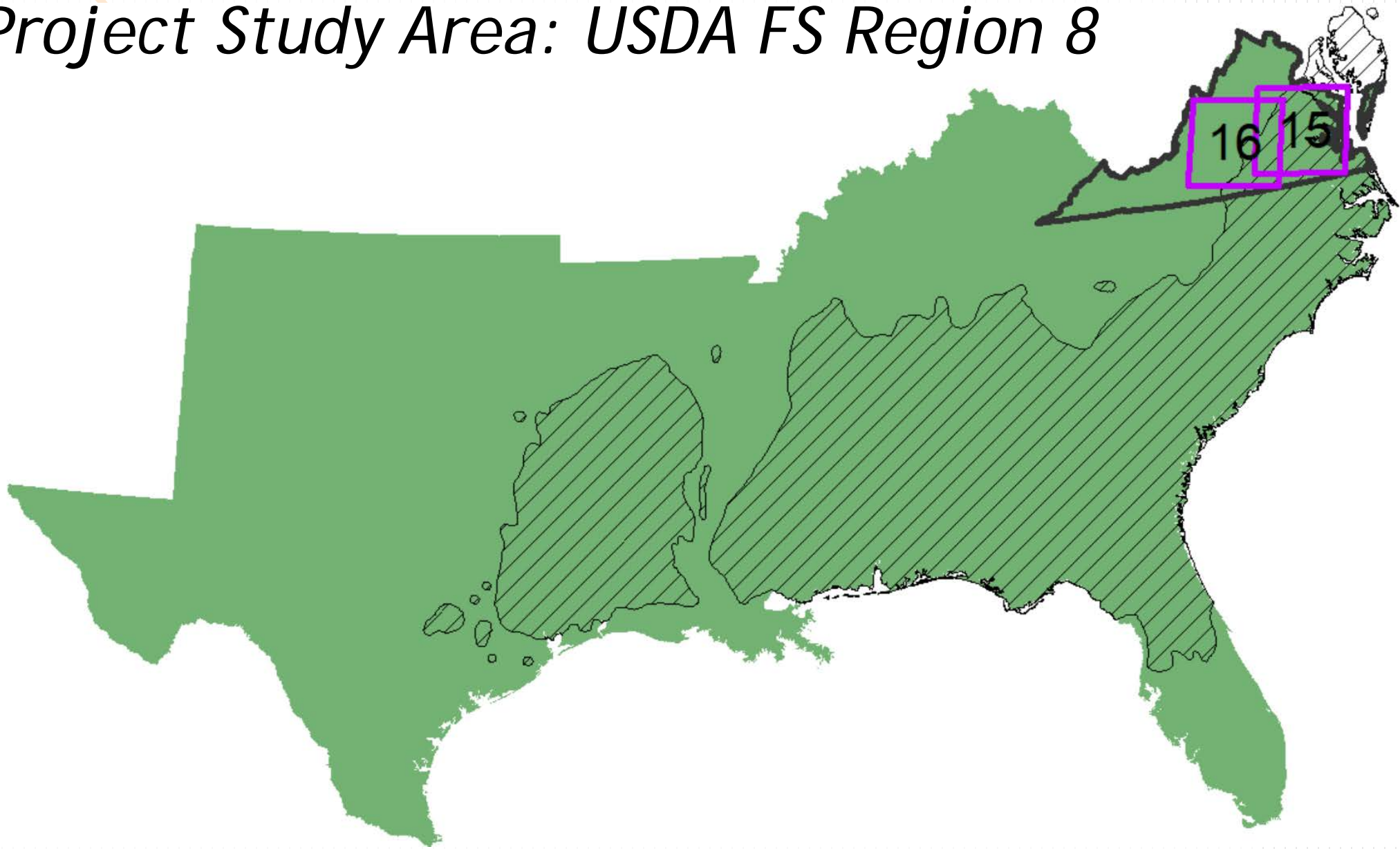


# *Overall project goal*

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- 
- To develop regionally refined land-use transition matrices that consider the economic structure of land management and land use decisions, incorporating forest management

*Project Study Area: USDA FS Region 8*



# *Mapping forest management and thins in Virginia*

V.A. THOMAS, R.H. WYNNE, J. KAUFFMAN,  
E. BROOKS, R.Q. THOMAS, L. CHINI, R. BIN  
MEI, D. WEAR, J. RAKESTRAW



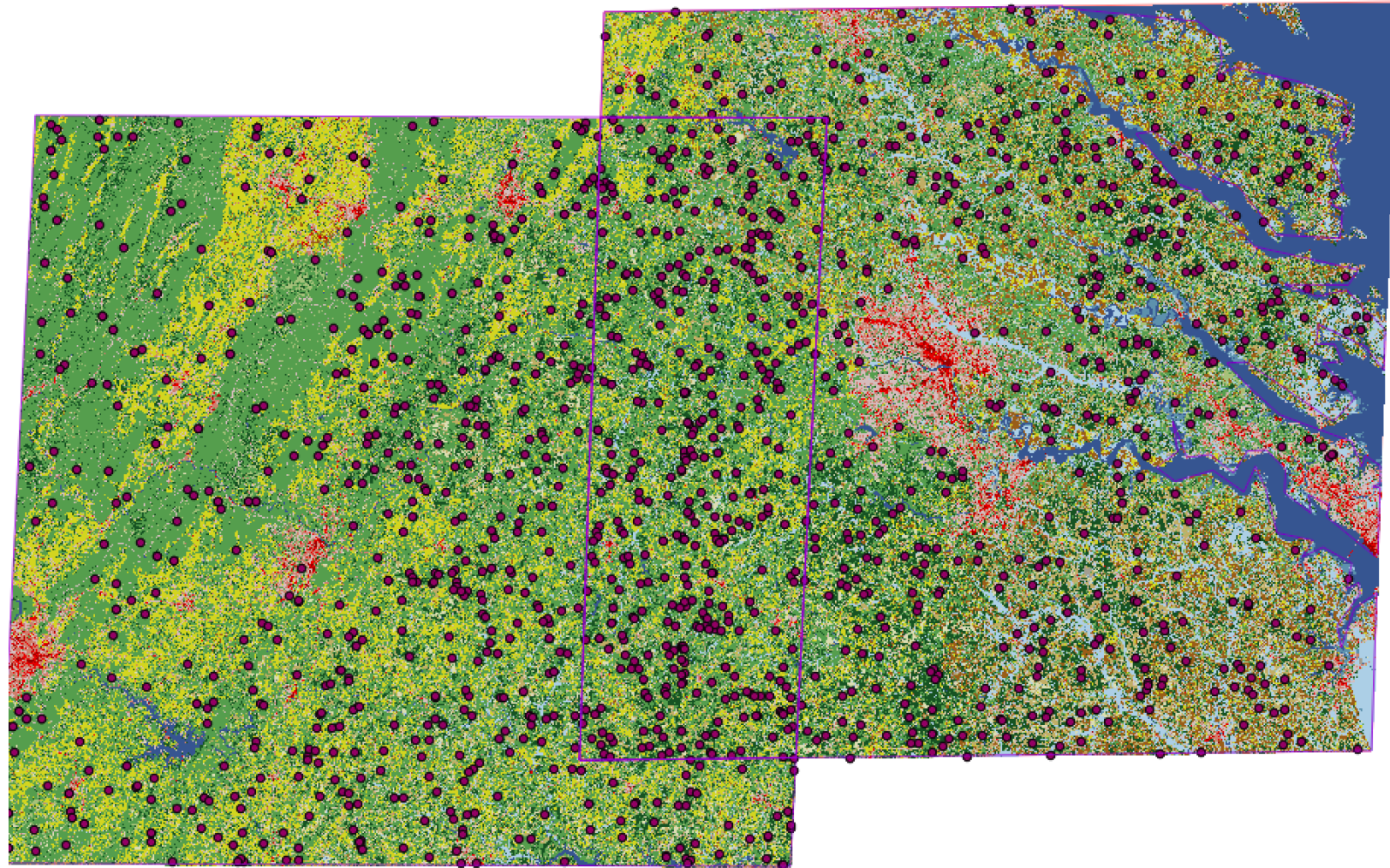


# *Developing a vetted subset of harvest records*

*Aug 2014-June 2017*

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- 1) Manual adjustment of coordinates from landing to stand
  - High resolution imagery in Google Earth
  - 1200 points
- 2) Development of a persistent pine class
  - Because only harvests are in the database
  - 300 points



# Predictor layers

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- HR constant, sine, cosine, RMSE, R2
  - 2009-11, 2014-16 [~156 acquisition dates]
  - L5 NDVI, L5 SWIR1, L5 SWIR2, L8 Pan (for 2014-16)
- 2011 NLCD, NLCD Change, CDL
- 2011 NLCD Tree Canopy Cover
- Hansen Global Forest Product
  - Loss year
  - Gain
  - Tree cover

} GEE for cloud-  
masking and  
EWMACD  
algorithm

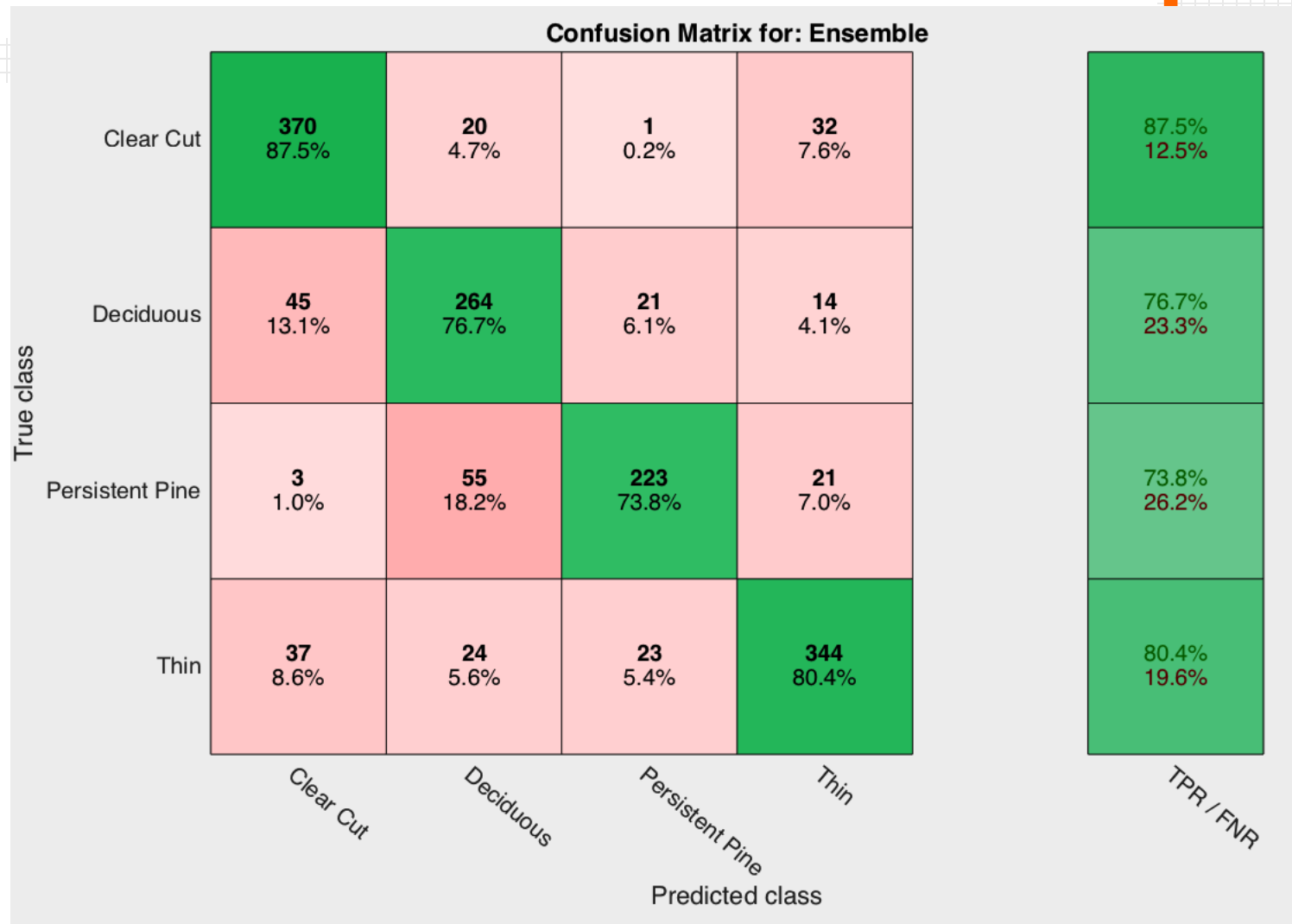
[https://earthenginepartners.appspot.com/science-2013-global-forest/download\\_v1.5.html](https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.5.html)

# Classification within CDL forest classes

(deciduous, mixed, coniferous, and woody wetlands)

(n samples=1497)

- Overall accuracy 80.2%
- 20 predictors
  - 2014-16 HR constant, sine, and cosine, R<sup>2</sup> and RMSE for NDVI, SWIR1, Pan
  - R<sup>2</sup> & RMSE for SWIR2
  - Hansen et al. loss year, tree cover, and gain



# Hansen et al (2013) and updated products (Loss year, tree cover, gain) by themselves

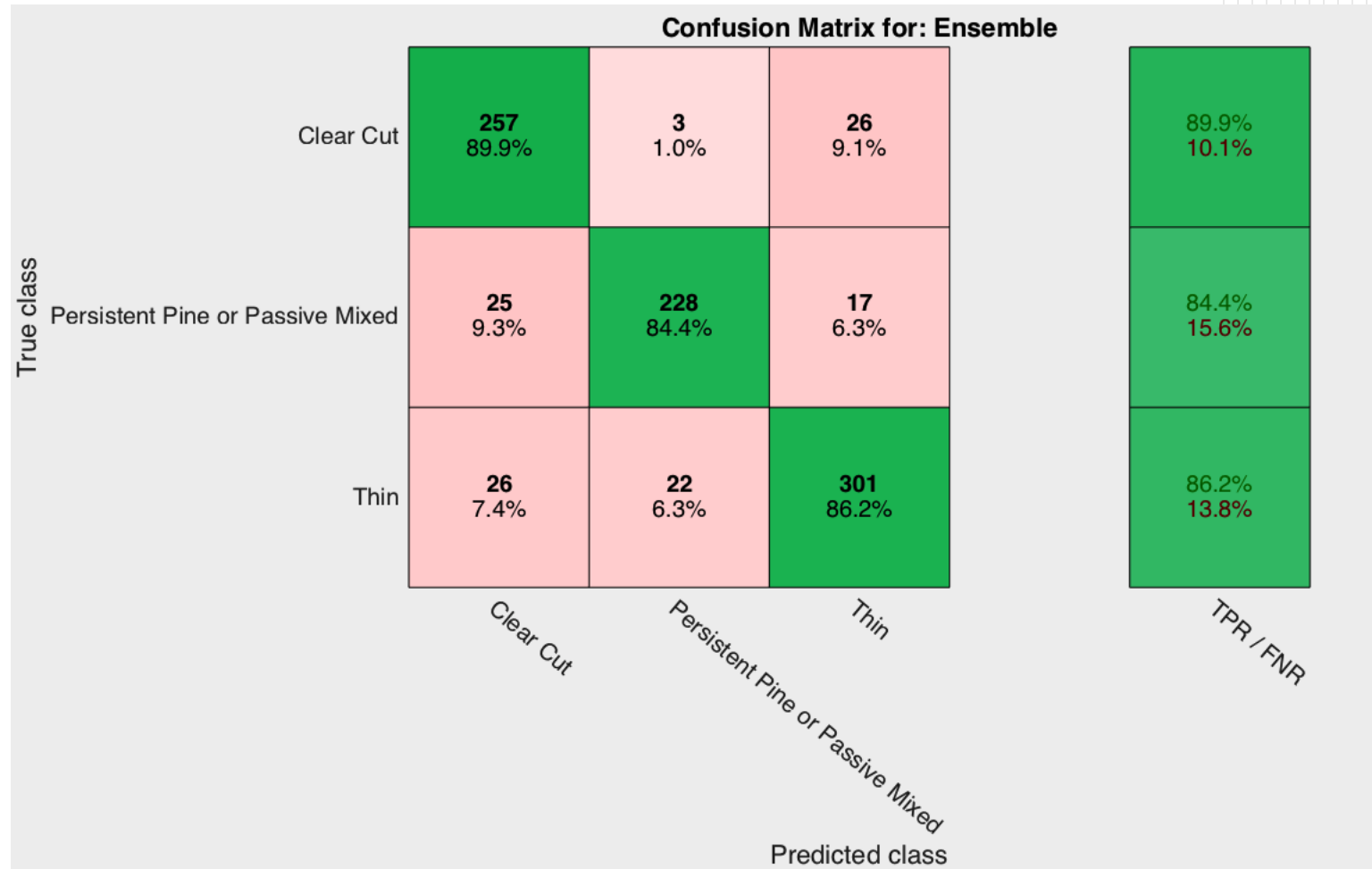
- Very valuable as predictor variables.
- Alone, 60% accuracy
  - 51% for thins
- Consistent with Breidenbach et al. (2018)

Confusion Matrix for: Ensemble

| True class      | Predicted class |              |                 |              | TPR / FNR      |
|-----------------|-----------------|--------------|-----------------|--------------|----------------|
|                 | Clear Cut       | Deciduous    | Persistent Pine | Thin         |                |
| Clear Cut       | 328<br>77.5%    | 4<br>0.9%    | 4<br>0.9%       | 87<br>20.6%  | 77.5%<br>22.5% |
| Deciduous       | 116<br>33.7%    | 187<br>54.4% | 33<br>9.6%      | 8<br>2.3%    | 54.4%<br>45.6% |
| Persistent Pine | 7<br>2.3%       | 120<br>39.7% | 168<br>55.6%    | 7<br>2.3%    | 55.6%<br>44.4% |
| Thin            | 112<br>26.2%    | 38<br>8.9%   | 60<br>14.0%     | 218<br>50.9% | 50.9%<br>49.1% |

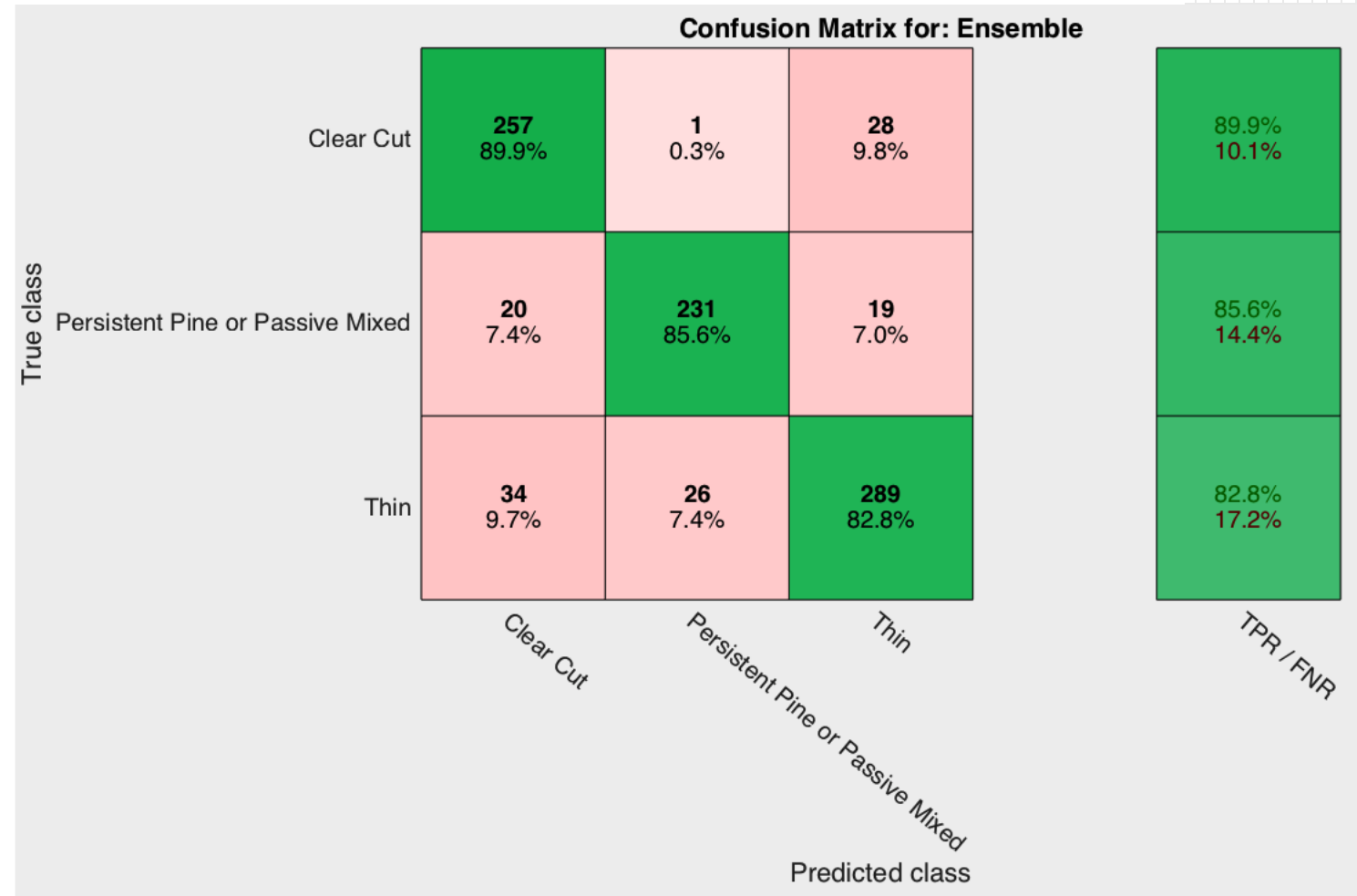
# Exclude the deciduous

- Combine
  - Passive mixed
  - Persistent Pine
- Overall accuracy 87%
  - Same 20 predictors



# Reduce Variables to 10 for mapping

- Overall Accuracy 86%
  - HR Constant, Sine, Cosine, R<sup>2</sup>, RMSE for Pan
  - R<sup>2</sup>, RMSE for NDVI 2014-16
  - Hansen et al. Loss year, tree cover, gain

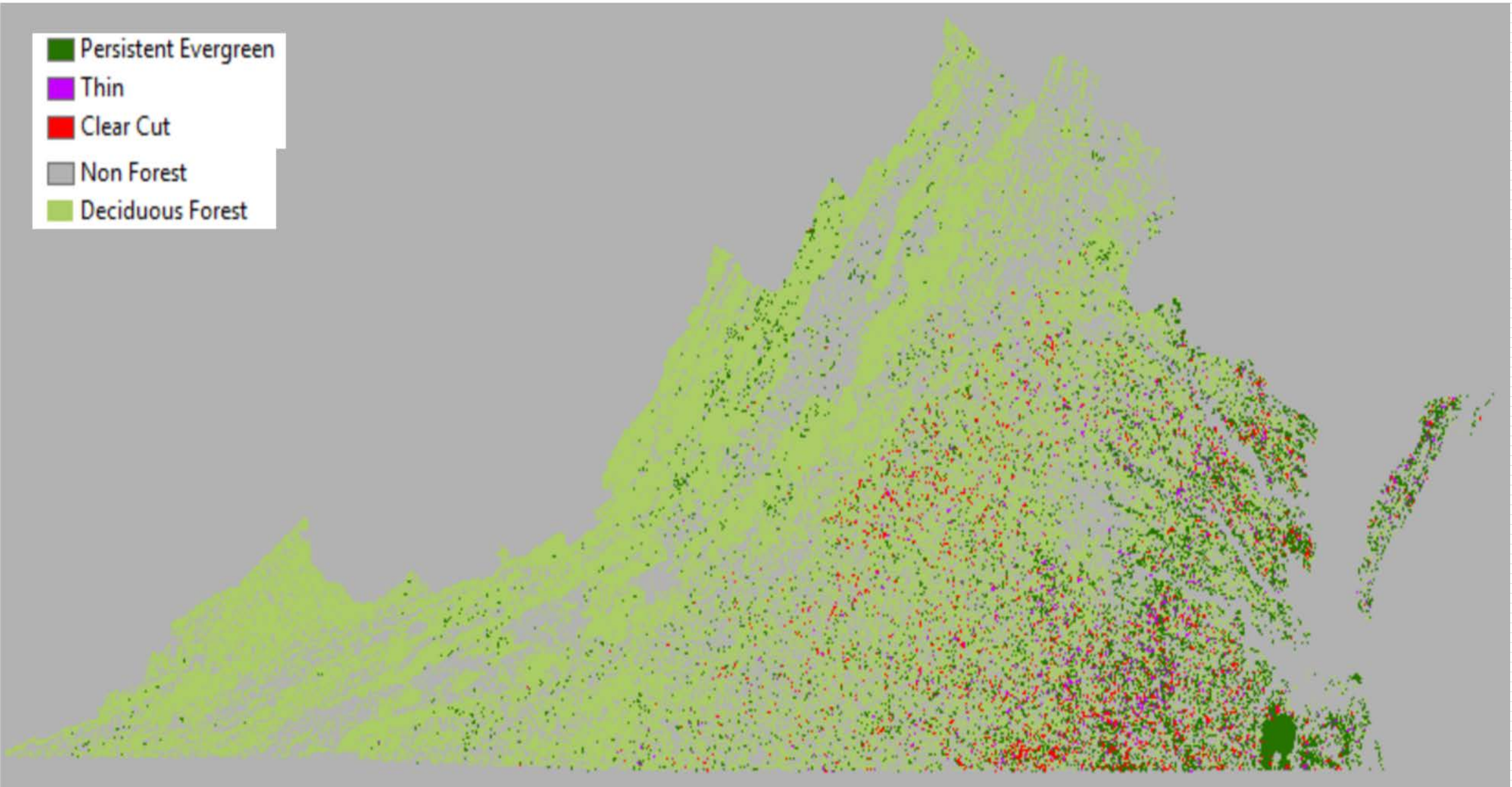


## *Development of a mask to apply to management classification*

|               | Commercial Selection | Non-harvested Pine | Thin | Clear Cut | Total |
|---------------|----------------------|--------------------|------|-----------|-------|
| NLCD          | 93.8                 | 96.7               | 76.1 | 89.1      | 87.8  |
| NLCD + change | 95.7                 | 96.7               | 79.6 | 91.6      | 90    |
| CDL           | 97.7                 | 99.7               | 94.1 | 98.4      | 97.2  |

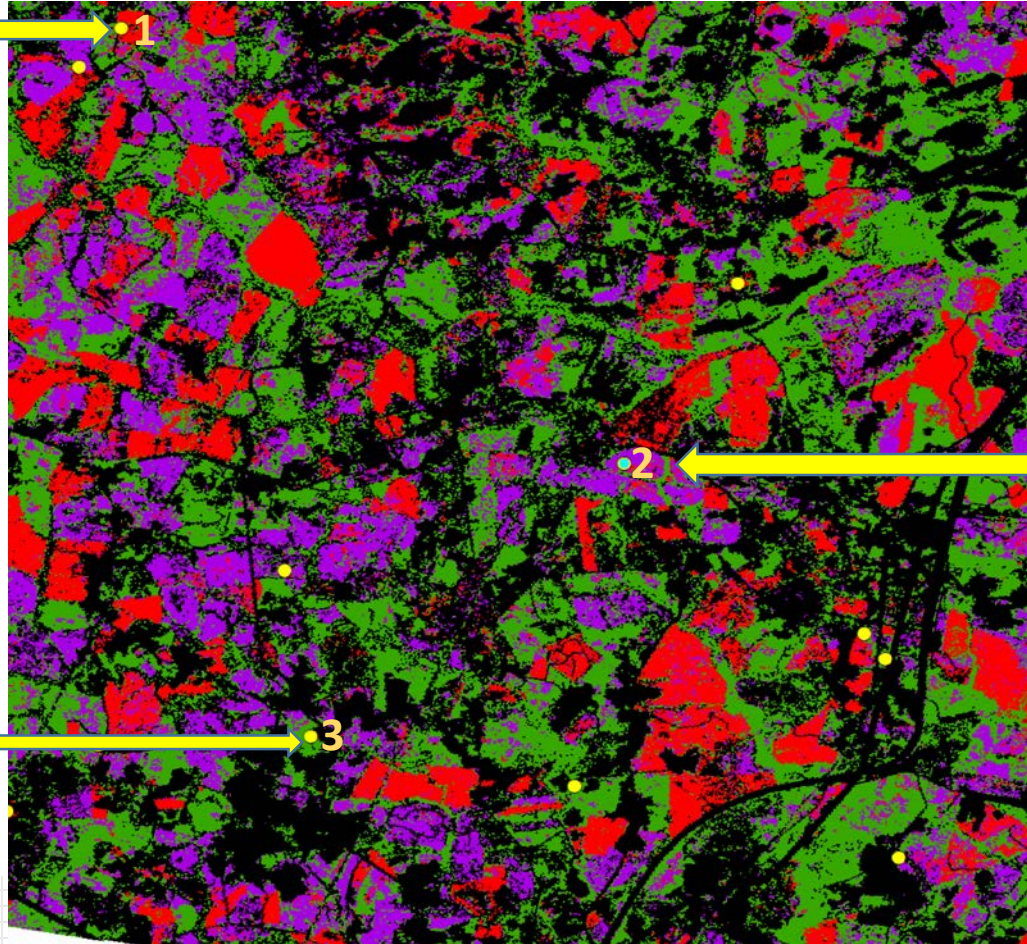
- NLCD classes: 41, 42, 43, 90
- CDL classes: 141, 142, 143, 190
- Maximize amount of thins captured by forest classes

- Persistent Evergreen
- Thin
- Clear Cut
- Non Forest
- Deciduous Forest

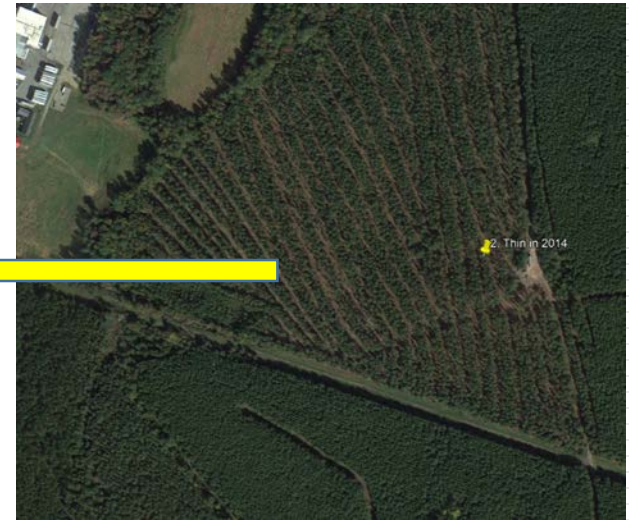




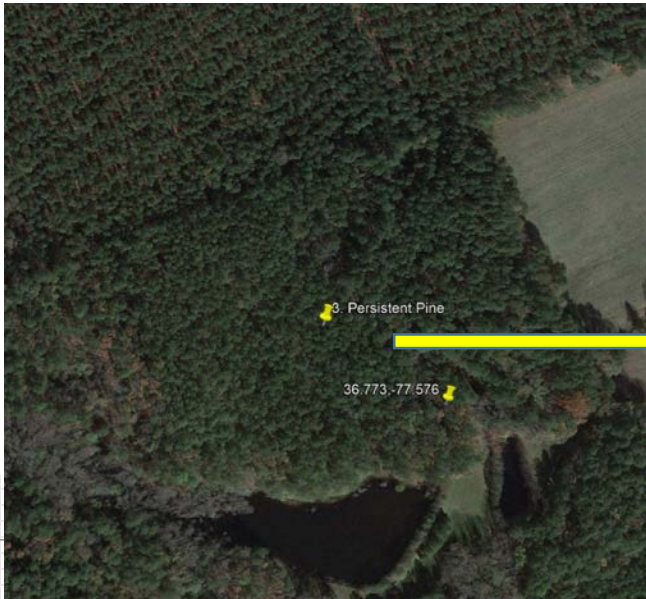
Clear Cut in 2014



2014 Thin



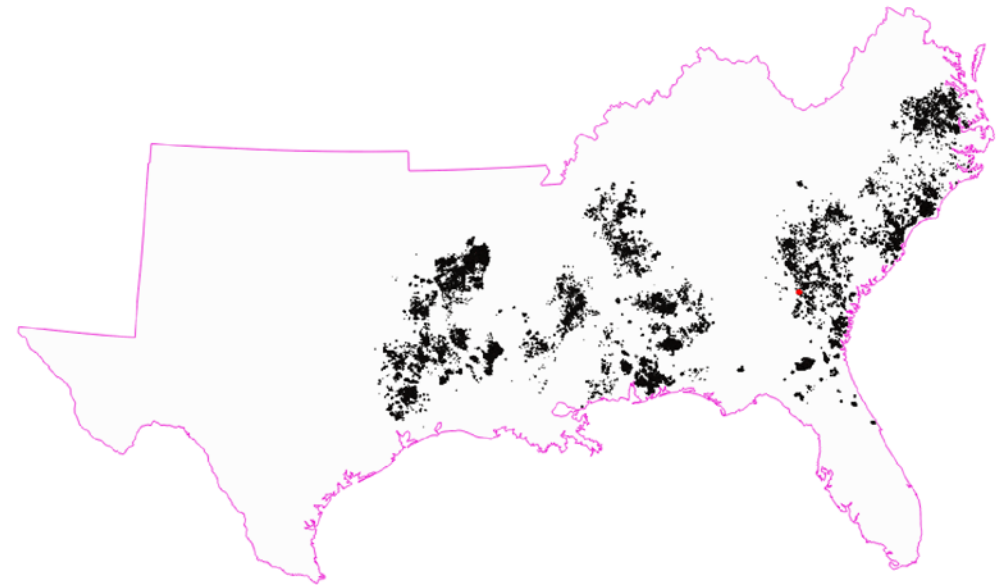
Persistent Pine



# *Implications of forest management mapping progress to date*

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- Single-harmonic fourier regression valuable predictors for forest thins.
- The Hansen et al. (2013) global forest product layers were valuable predictors in our algorithm
  - Not sufficient for thins on there own
- High-resolution panchromatic band in Landsat 8 valuable
- High performance computing needed



# *Forest management and LAI*

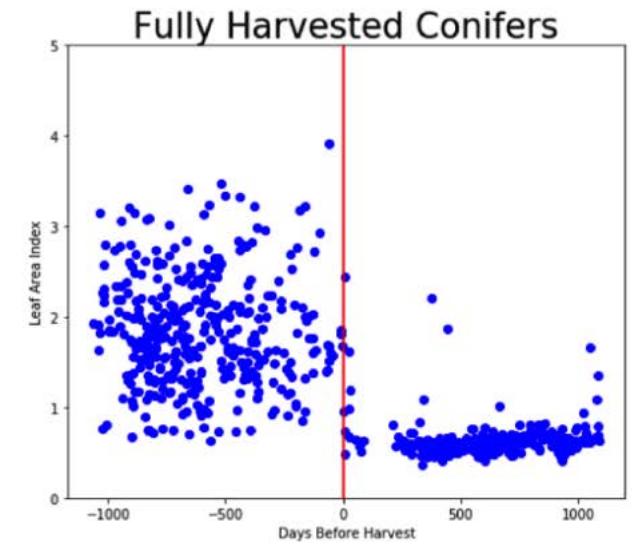
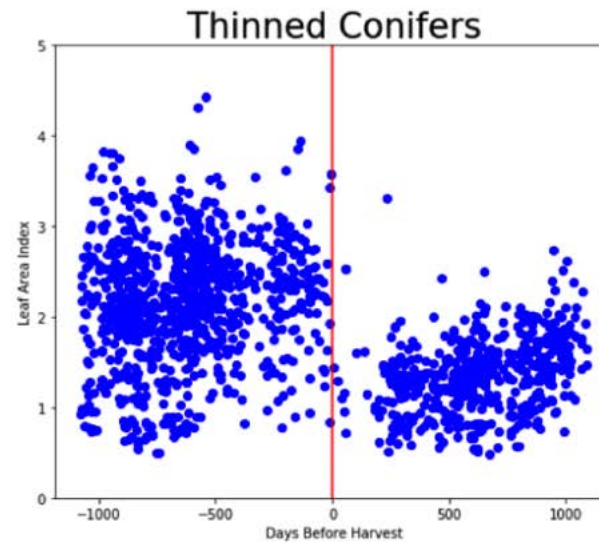
Blinn, C.E., M.N. House, R.H. Wynne, V.A. Thomas, T.R. Fox, and M. Sumnall. 2019. Landsat 8 based leaf area index estimation in loblolly pine plantations. *Forests*. 10(3): 222; <https://doi.org/10.3390/f10030222>



# Management and LAI: Loss and Recovery

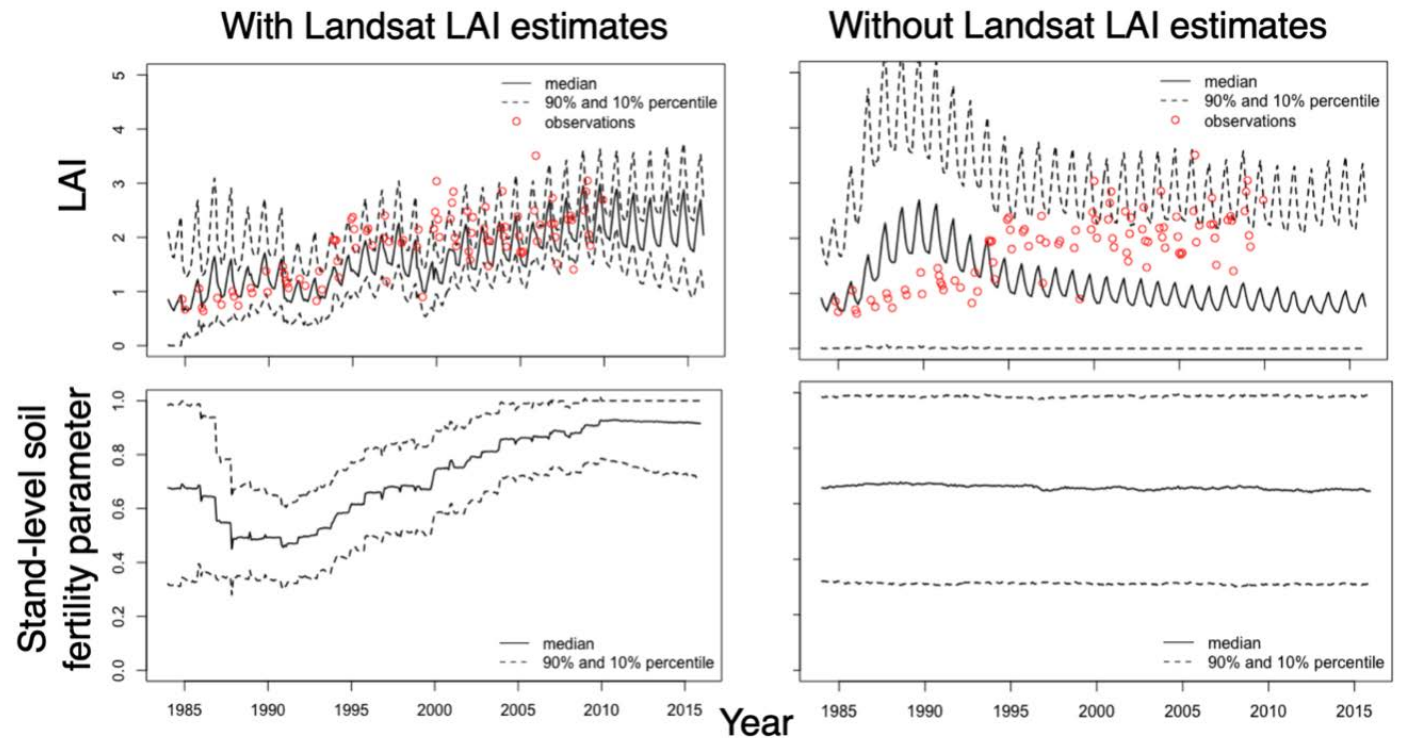
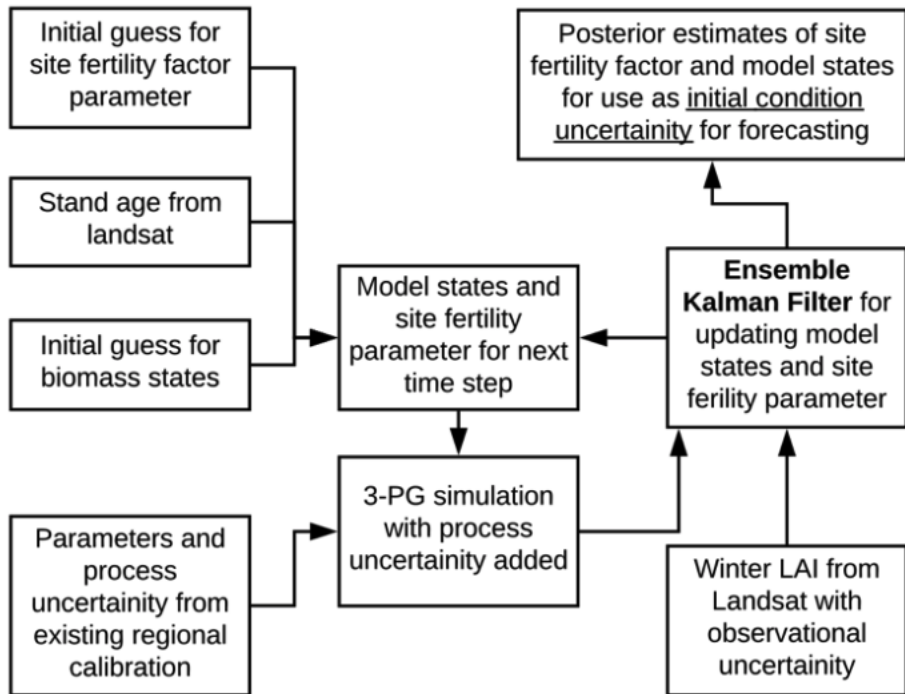
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- Loss and recovery
- Fertilization
- Understory and competition



# Landsat-LAI for regional projections of productivity and fertility

## Ensemble Kalman Filter approach



*Economic framework  
that incorporates  
biophysical and  
financial risk*

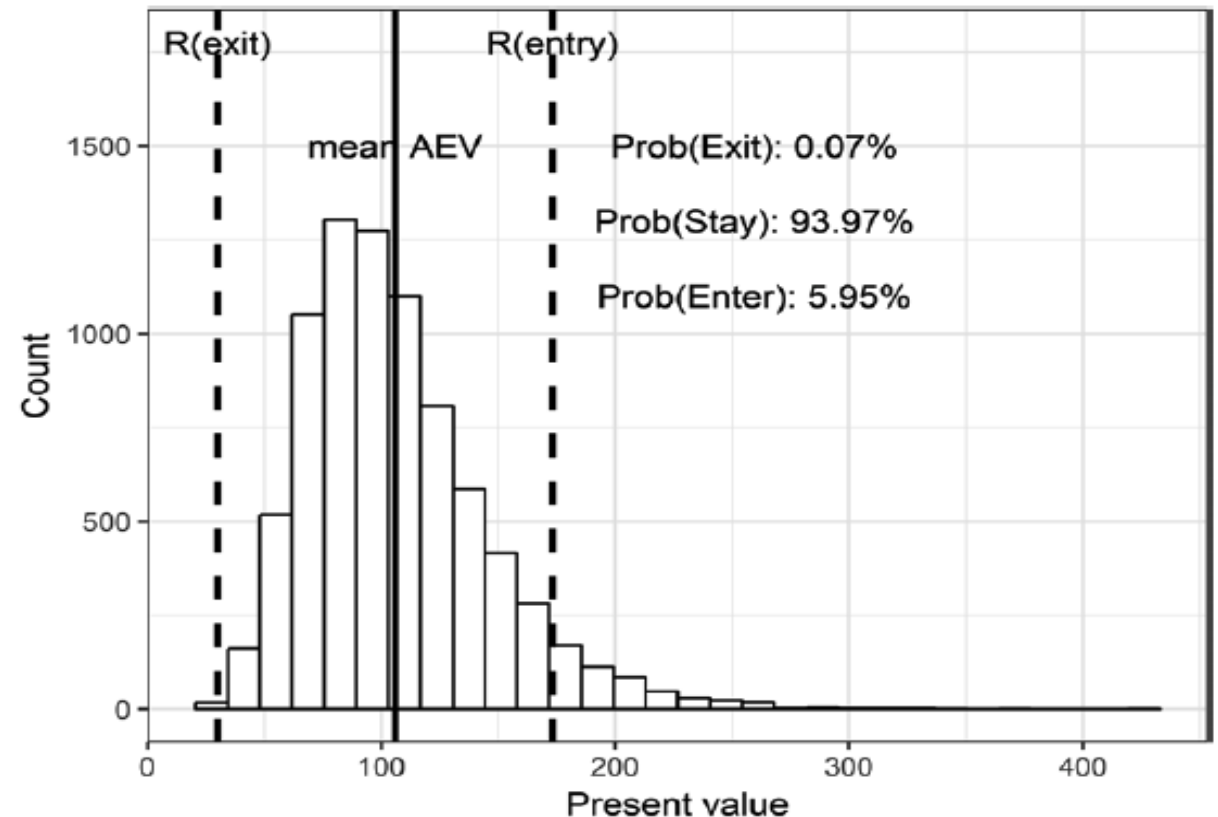
Mei, B., D. Wear, and J. Henderson. 2019. Timberland investment under both financial and biophysical risk. *Land Economics*, 95(2): 279-291.



# *Economic framework for land use transitions that includes biophysical and financial risk*

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- blend stochastic processes for prices and net yields within a real options framework that accounts for the temporal structure of forest production
- Timber Mart-South (TMS) timber price data
- 3-PG models of growth and yield for 20 global circulation models (GCMs) based on the RCP 8.5 emissions scenario
- Monte Carlo simulations to incorporate both financial and biophysical risk
  - geometric Brownian motion (GBM) stochastic function
  - examined the optimal entry and exit opportunities of timberland investment in 10 southern states in the United States.
  - Mostly “hold”
  - Slight upward trend in investment



# Synthesis and Intercomparisons

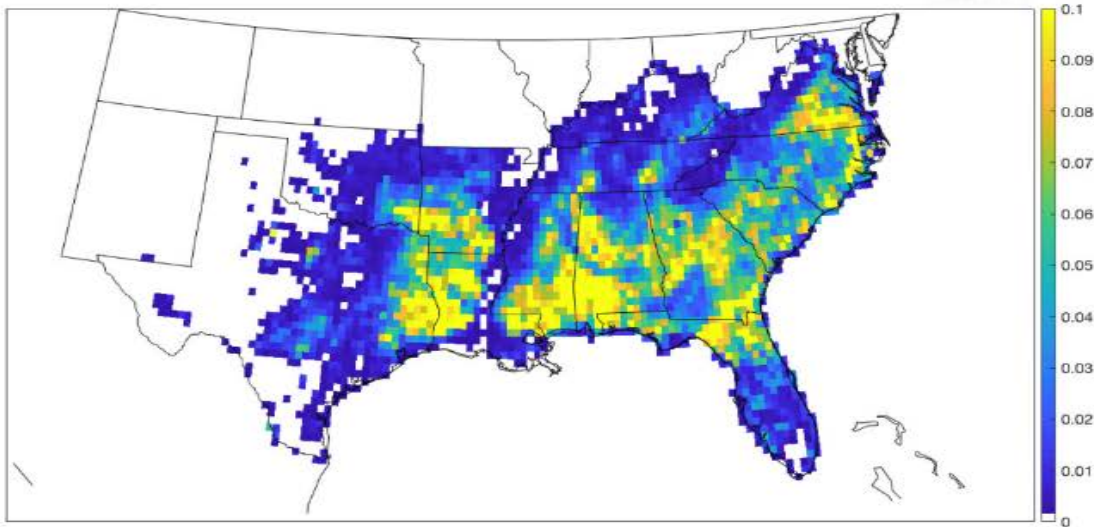
- Synthesis of
  - Landsat classifications
    - At GLM scale
  - Southern Forest Futures
    - At GLM scale
  - GLM Land Use transition matrices
- Establish a baseline to quantify the impact of regionally-specific land use transition matrix.

| GLM Class             | NLCD Class  |
|-----------------------|---|
| Urban                 | 21 Developed, Open Space<br>22 Developed, Low Intensity<br>23 Developed, Medium Intensity<br>24 Developed High Intensity                                      |
| Crop Functional Types | 82 Cultivated Crops   |
| Managed Pasture       | 81 Pasture/Hay  |
| Rangelands            | 71 Grassland/Herbaceous   |
| Primary Non-Forest    | 31 Barren Land (Rock/Sand/Clay)   |
| Secondary Non-Forest  | 11 Open Water<br>12 Perennial Ice/Snow<br>51 Dwarf Scrub<br>52 Shrub/Scrub<br>72 Sedge/Herbaceous<br>73 Lichens<br>74 Moss<br>95 Emergent Herbaceous Wetlands |
| Secondary Forest      | 41 Deciduous Forest<br>42 Evergreen Forest<br>43 Mixed Forest<br>90 Woody Wetlands  |

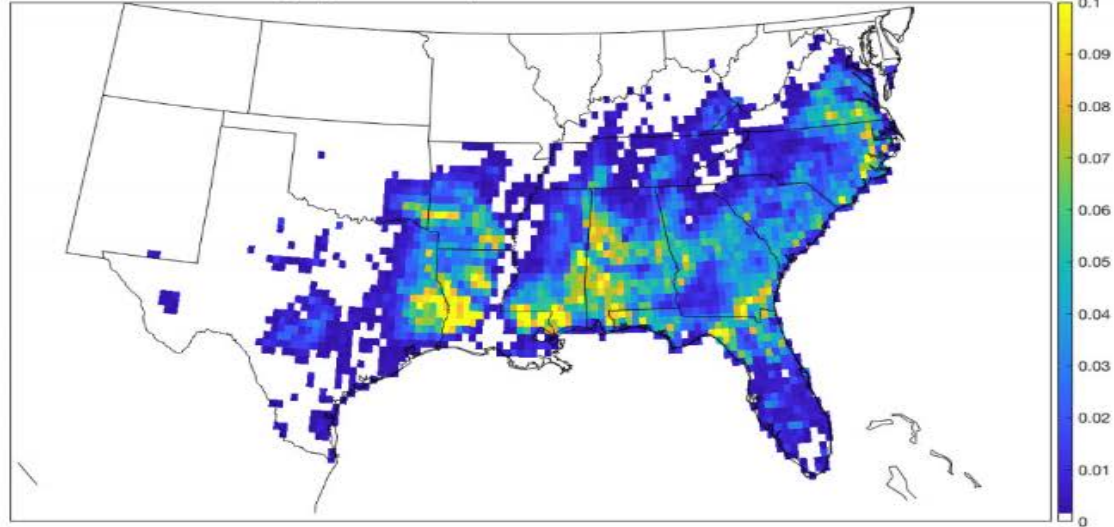


# 2001 to 2011

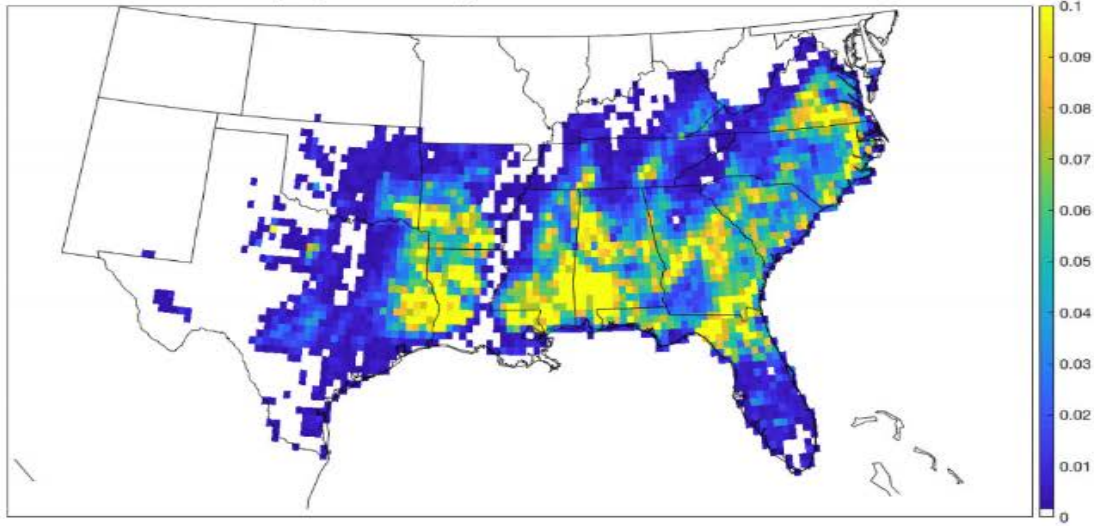
NLCD, all transitions away from secondary forest



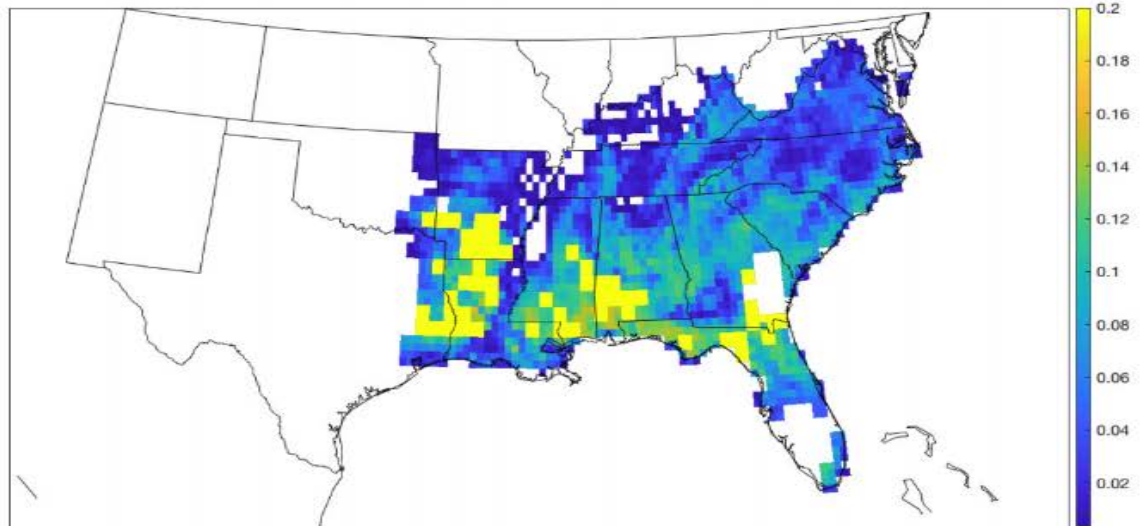
NLCD, transitions from secondary forest to secondary/primary non-forest



NLCD, transitions from secondary forest to secondary/primary non-forest and rangeland



LUH wood harvest (from forest) area



# Next steps

- Complete the regional analysis of thins and management based on the management classification techniques described above.
- Incorporate Landsat-derived land use transitions from production forestry as a separate new class in the LUH/GLM.
- Upscaling the Southern Forest Futures projections to the GLM to finalize the baseline comparison between the GLM, NLCD, and Southern Forest Futures land use transition matrices.
- Conduct intercomparison of (three) with land use transitions described by Landsat-based models, economic projections that incorporate risk, and the GLM.
- Continue to disseminate results.



# *Questions?*

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Forest Resources & Environmental Conservation

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International Paper